Decision Trees for Uplift Modeling

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Decision trees for uplift modeling

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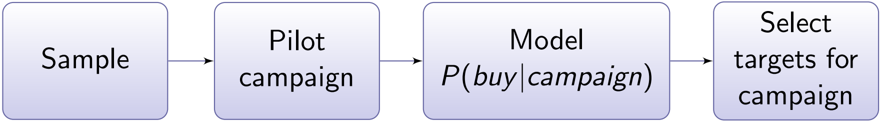
ICDM 2010

Marketing campaign example



Main idea of uplift modeling

We can divide objects into four groups

1. Responded **because** of the action
2. Responded **regardless** of whether the action is taken (**unnecessary costs)**
3. Did not respond and the action had **no impact** (**unnecessary costs)**
4. Did not respond **because** the action had a **negative impact** (*e.g.* customer got annoyed by the campaign, may even churn)

Traditional classification vs. uplift modeling

Traditional models predict the conditional probability

$$P(response|treatment)$$

Traditional classification vs. uplift modeling

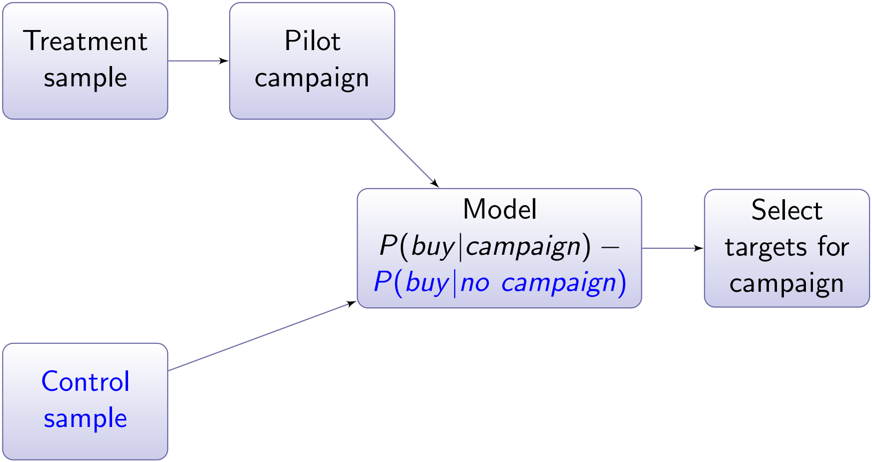
Traditional models predict the conditional probability

$$P(response|treatment)$$

Uplift models predict change in behaviour resulting from the action

$$P(response|treatment) - P(response|no\ \ treatment)$$

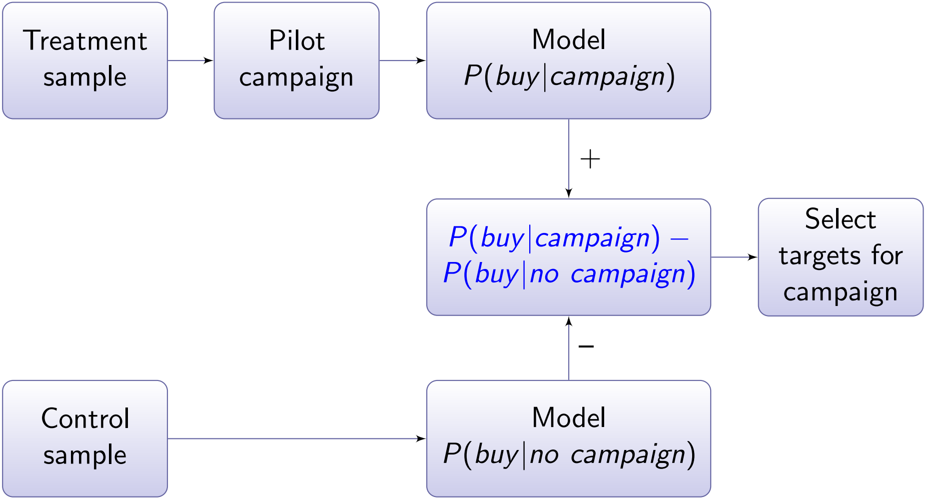
Marketing campaign example (uplift modeling approach)



Related work

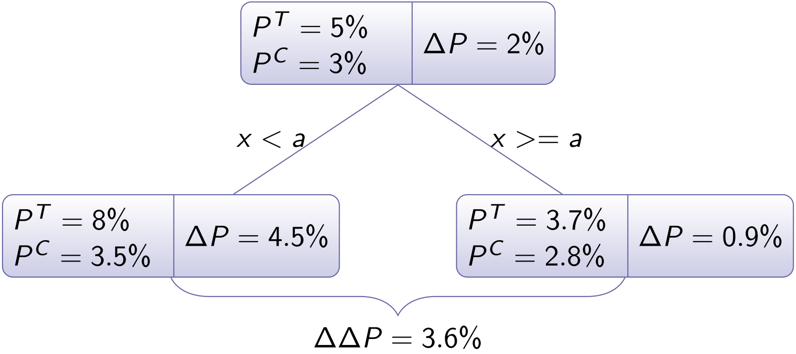
- Literature
  - Surprisingly little attention in literature
  - Business whitepapers offering vague descriptions of algorithms used
- Two general approaches
  - Subtraction of two models
  - Modification of model learning algorithms

Subtraction of two models



Current approaches to uplift decision trees

- Create splits using difference of probabilities ($\Delta\Delta P$)



- Pruning not used (or not described)
- Work only for two class problems and binary splits

Our approach to uplift decision trees

- Spliting criteria based on **Information Theory**
- **Pruning** strategy designed for uplift modeling
- **Multiclass** problems and multiway splits possible
- If the **control group is empty**, the criterion should reduce to one of classical splitting criteria used for decision tree learning

Kullback-Leibler divergence

- Measure difference between treatment and control groups using KL divergence

$$KL\left(P^T(Class) : P^C(Class)\right) = \sum_{y \in \mathrm{Dom}(Class)} P^T(y) \log \frac{P^T(y)}{P^C(y)}$$

Kullback-Leibler divergence

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- Need KL-divergence conditional on a given test

$$KL(P^T(Class) : P^C(Class) | Test) = \sum_{a \in \mathrm{Dom}(Test)} \frac{N^T(a) + N^C(a)}{N^T + N^C} KL\left(P^T(Class|a) : P^C(Class|a)\right)$$

Measures how much the two groups differ given a test's outcome

Final splitting criterion

$$KL_{gain}(Test) = KL\left(P^T(Class) : P^C(Class) | Test\right) - KL\left(P^T(Class) : P^C(Class)\right)$$

- Measures the *increase* in difference between treatment and control groups from splitting based on *Test*
- If the control group is empty, KL_{gain} reduces to entropy gain

Final splitting criterion

$$KL_{gain}(Test) =$$
$$KL\left(P^T(Class) : P^C(Class) | Test\right) - KL\left(P^T(Class) : P^C(Class)\right)$$

- Measures the *increase* in difference between treatment and control groups from splitting based on *Test*
- If the control group is empty, KL_{gain} reduces to entropy gain

$$KL_{ratio} = \frac{KL_{gain}(Test)}{KL_{value}(Test)}$$

- Tests with **large number of values** are punished
- Tests which split the control and treatment groups in **different proportions** are punished
- Postulates are satisfied

Splitting criterion based on squared Euclidean distance

$$Euclid\left(P^T(Class) : P^C(Class)\right) = \sum_{y \in \mathrm{Dom}(Class)} \left(P^T(y) - P^C(y)\right)^2$$

- $Euclid_{gain}$, $Euclid_{ratio}$ analogous to KL
- Better statistical properties (values are bounded)
- Symmetry

Pruning procedure (maximum class probability difference)

- Definitions

$$Diff(Class, node) = P^T(Class|node) - P^C(Class|node)$$

- Maximum class probability difference (MD)

$$\begin{aligned} MD(node) &= max_{Class} \left|Diff(Class|node)\right| \\ sign(node) &= \operatorname{sgn}(Diff(Class^*, node)) \end{aligned}$$

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- Use separate validation sets
- Bottom up procedure
- Keep subtree if
  - On validation set: *MD* of the subtree is greater than if it was replaced with a leaf
  - **And** the sign of *MD* is the same in training and validation sets

Experimental evaluation

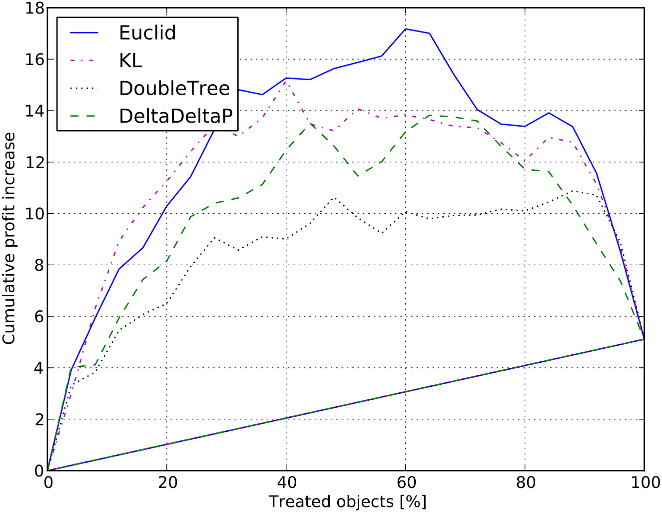
- Compared models

1. **Euclid** - uplift decision trees based on E_{ratio}
2. **KL** - uplift decision trees based on KL_{ratio}
3. **DeltaDeltaP** - based on the $\Delta\Delta P$ criterion
4. **DoubleTree** - separate decision trees for the treatment and control groups

Method of evaluating uplift classifiers

- Control and treatment datasets are scored using the same model
- Compute **lift curves** on both datasets
- **Uplift curve** = lift curve on treatment data – lift curve on control data
- Measure model's performance based on
  - Area under the uplift curve (AUUC)
  - Height of the uplift curve at the 40th percentile

The uplift curve for the splice dataset



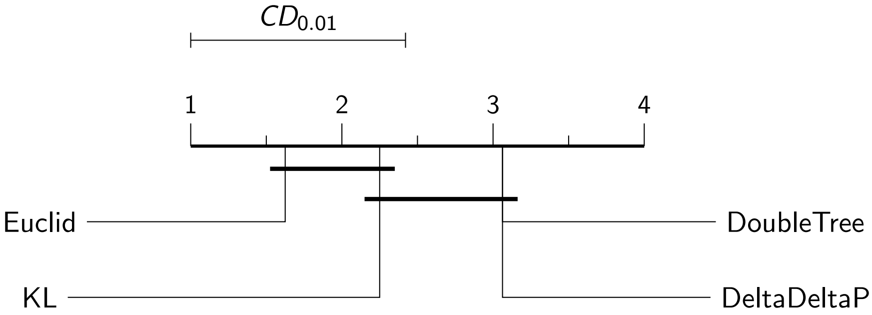
Data preparation

- Lack publicly available data to test uplift models
- Datasets from UCI repository were split into treatment and control groups based on one attribute
- Procedure of choosing the splitting attribute:
  - If an action was present it was picked (e.g. hepatitis data)
  - Otherwise pick the first attribute which gives a reasonably balanced split

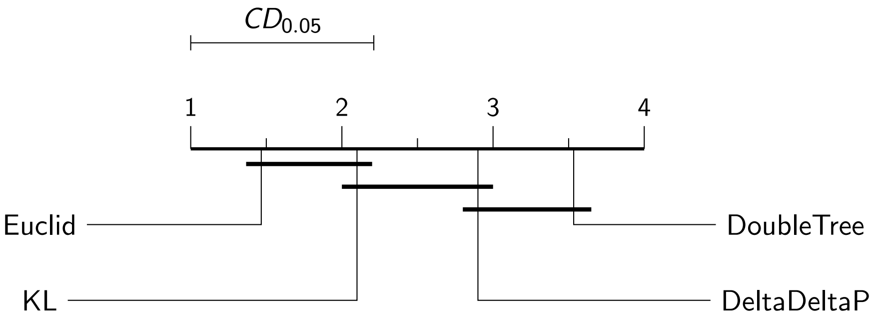
Methodology of model comparision

1. Models are evaluated using 2×5 **crossvalidation**
2. Models are compared by ranking on all datasets
3. Check if there are differences in model prformance using **Friedman's test**, a nonparametric analogue of ANOVA
4. If the test shows significant differences, a post-hoc **Nemenyi test** is used to assess which of the models are significantly different

Results for Area Under Uplift Curve
Nemenyi test at $p = 0.01$



Results for the height of the curve at the 40th percentile Nemenyi test at $p = 0.05$



Summary

- Method for decision tree construction for uplift modeling in the style of modern decision tree learning
  - Information Theory based splitting
  - Dedicated pruning strategy
- Two splitting criteria (KL and Euclidian distance)
- Reduce to standard decision trees if control data absent
- The new method significantly outperforms previous approaches to uplift modeling
- Other applications e.g. medicine